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Impact of public and private research *funding* on scientific production: The case of nanotechnology

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Abstract

This article measures the impact of public grants, private contracts and collaboration on the scientific production of Canadian nanotechnology academics. The paper estimates a time-related model of the impact of academic research financing and network structure on the research output of individual academics measured by the number of papers. Results suggest that the effect of individual public funding follows a J-shaped curve. Although contracts have no effects, the impact of patenting follows an inverted-U shaped curve. In addition, a strong central position in the past collaborative network has a positive effect on research output.

Keywords: Scientific articles; Public research funding; Contracts; Patents; Innovation networks; Nanotechnology

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1 Introduction

The financing of university research is being scrutinized in Canada and elsewhere as governments increasingly demand measures of impact and outcomes from grant awarding bodies. One such impact is scientific output: Payne and Siow (2003) as well as Blume-Kohout et al. (2009) for instance show that the public funding of university research has a positive effect on university scientific production. As Gibbons et al. (1994) suggest, the direction of research has migrated from a discipline-based science free of societal needs to a more demand driven science that must meet certain objectives. The integration of university research financing with government programs aimed at the stimulation of innovation is a relatively recent phenomenon (Link and Scott, 2004), but a strategy that is used more and more. This is especially true for domains seen as potential growth generators such as aerospace, biotechnology and lately nanotechnology. Innovation incentives such as R&D tax credits have been put in place and university researchers have benefitted from increased links with industry as a consequence in the form of research contracts.

While public research grants are generally associated with wide scope projects, private contracts concentrate on short-term objectives aiming at the production of knowledge that can rapidly be used (Goldfarb, 2008). Gulbrandsen and Smeby (2005) find a positive correlation between private financing of Norwegian academics and the number of articles they publish. Not only are these university researchers more productive, their work is more applied and they collaborate more with other academics and with industrial researchers. Van Looy et al. (2004) find similar results for contracting activities of researchers.

Both publicly funded research and private contracting activities may lead to patenting. The literature generally finds that academics who patent produce more scientific publications (Breschi et al., 2005; Calderini and Franzoni, 2004; Calderini et al., 2007; Meyer, 2006; Van Looy et al., 2006) or that there is no significant effect (Agrawal and Henderson, 2002). Balconi and Laboranti (2006) show that researchers that are named inventors on patents owned by firms publish more than their colleagues. Although it is not the prime aim of this paper to investigate whether patenting is detrimental to scientific publication performance, our model allows us to crudely contribute to the debate.

As funding does not generally come to single researchers but mainly to teams of researchers, the other issue that this paper wishes to discuss is the influence of collaboration, measured for instance by the position of individual scientists within their co-publication network, on individual scientific production. Lee and Bozeman (2005) find that US researchers who collaborate generally produce more scientific articles than researchers working alone. Other authors find similar results for the UK (Katz and Hicks, 1997) and for Quebec (Landry et al., 1996). International collaboration increases the potential to publish and to publish in international mainstream journals (Barjak and Robinson, 2007; Martín-Sempere et al. 2002). To our knowledge, however, very little or no literature examines the influence of individual indicators of the position of scientists within the collaboration network on scientific production.

This article thus integrates the literature on university research funding and on innovation networks. Following in the footsteps of the literature, our goal is then to estimate the influence of publicly and privately funded research on the production of scientific articles controlling for the collaborative network position of the researchers and taking into account the university affiliation of the scientists. As such, we aim to answer the following questions: Do better-funded scientists produce more articles? Does contracting and working with industry slow down this productivity? Are better-connected scientists more productive?

The remainder of the paper proceeds as follows: section 2 describes the conceptual framework including a brief review of the literature; section 3 presents the data and methodology; section 4 presents various summary statistics of the data; section 5 presents and analyses the regression results; and finally, section 6 concludes.

2 Conceptual framework

A great number of scientific publications have been published in nanotechnology during the last two decades (see for instance the review by Palmberg et al., 2009, and the country comparison studies by Youtie et al., 2008). The observation of this rapid rate of growth in nanotechnology since 1990 is further supported by Bonaccorsi and Thoma (2007). It is thus a multidisciplinary field that has created a rich pool of publications in all these different disciplines (Porter et al., 2008 and Mogoutov and Kahane, 2007 have developed specific keyword searches for different subdomains).

As such, nanotechnology has potential applications in a wide range of domains, from nanomaterials to nanoelectronics, and from nanofoods to nanobiotechnology. Lipsey et al. (2005) and Youtie et al. (2008) indeed suggest that nanotechnology may be the next general purpose technology, i.e. the next engine of growth of the 21st century.

As an emerging technology, nanotechnology innovation goes through different phases of development. For the first phase, the patience required and the uncertainties linked to the innovation process do not suit all types of fund providers, hence the importance of public research in these domains. Collaboration with university research centers contribute to reducing the uncertainties of innovation activities and thus the risks related to R&D projects. Public financing of research thus facilitates the production of knowledge and constitutes one of the key elements of the development of high-tech innovation. Research funding therefore enhances the success of innovation.

Zucker et al. (2007) insist on the necessity of collaboration between institutions to foster information exchange. Multi-project research centers force researchers and their universities to collaborate more efficiently using the diversity of resources available. Collaboration can indeed become a powerful lever to raise funds (Daniel et al., 2003), and scientific collaboration and research funding are consequently intrinsically intertwined.

Nanotechnology research requires an important infrastructure in order to realize the projects that lead to the development of new products or processes (Robinson et al., 2007), even more so than for biotechnology. Infrastructure investment not only consists of the acquisition of complex machines and instruments but also of the funds necessary for their operation and maintenance that requires specialized skilled personnel and logistics management to optimize access to this infrastructure. The creation of such a technological platform hence requires long-term investment in order to play its role as a space that fosters the emergence and fulfillment of new opportunities. Although universities and their affiliated research centers are the natural candidates for the localization of such technological platforms, because their main goal is often to generate knowledge aimed at yielding technological innovation, the private sector should play an important role in their management and utilization.

Intuitively, most university research projects are financed from public funds (Hagedoorn et al., 2000). Hart (2001) recognizes that public financing is increasingly targeted towards the development of innovation according to specific political guidelines; the main objective of these political guidelines being the creation and maintenance of competence centers within the university network. This network, composed of universities and their affiliated research centers, is an integral part of the national system of innovation (Hall et al., 2003). Within the national system of innovation, universities and their affiliated research centers play a crucial role in the innovation value chain that leads to economic growth (Link and Scott, 2004; Zucker et al., 2002). For instance, public research infrastructure generates technological knowledge that is transferred via pure externalities, entrepreneurship or contracts (Zucker *et al.*, 1998). University researchers facilitate knowledge transfer between research laboratories and firms (Audretsch and Stephan, 1996). All these beneficial effects have a common origin: money and to a certain extent, collaborative work.

Payne and Siow (2003) as well as Blume-Kohout et al. (2009) suggest that the augmentation in public financing that university science research has experienced recently has had a tremendous effect on scientific output. Furthermore, public funding for specific projects can be perceived as a signal of quality not only for the funded researchers, but also for their university. Adams et al. (2005) show that top universities and departments that have earned awards, have larger teams (with an increased scientific division of labor at the international level) and have more government funding.

The granting of research money further act as a signal that attracts additional funding in subsequent years. Using a static model, Arora et al. (1998) show that the publication track record of researchers has an influence on future grants and consequently on future publication levels as well. Zucker et al. (2007) generally show the major impact that research financing has both on the publication of scientific articles and on patent production. Specifically, Payne and Siow

(2003) show that three years after receiving an instrumentation grant of one million dollars, between 8 and 11 new articles are generally published annually. Jacob and Lefgren (2007) find that specific grants contribute to adding one additional publication within the five years subsequent to the attribution of the grant.

Proposition 1: Academics that obtain greater amounts of public funding generate a larger number of articles.

In a field as close to its science base as nanotechnology, public financing should be seen as complementary to private contracts. Private funding has dramatically increased since 1985 (Cohen *et al.*, 2002) and so did university-industry research centers. University-industry research relations increase contact with scientists but lower communication between scientists and possibly shield their work from potentials future partners (Welsh et al., 2008). As a consequence, a greater proportion of contracts could have a negative effect on a scientist's future scientific production. This could be due to the different reward process used in industrial and academic milieus (Owen-Smith *et al.*, 2001), or to the short-termism associated with private contracts (Goldfarb, 2008). Despite these findings, Blumenthal et al. (1996), Gulbandsen and Smeby (2005) as well as Van Looy et al. (2004) find that contracts have a positive effect on knowledge production. In fact, an overwhelming body of evidence finds a positive relationship between 'academic enterprise' and scientific performance (see the excellent review of Larsen, 2011 for a complete survey).

Proposition 2: Receiving greater amounts of research funds from contracts is beneficial to the scientific productivity of an academic.

Knowledge used within these research institutions, is often appropriated from the publications generated by the research community (Dasgupta and David, 1984). Knowledge generated (output) by some scientists thus becomes knowledge appropriated (input) by other scientists. The notion of knowledge networks is clearly appropriate to the analysis of such a positive feedback system or virtuous circle. Their importance both in terms of economic growth and codified knowledge diffusion has been demonstrated (Aharonson et al., 2004), and a number of authors use social network analysis and network indicators emanating from graph theory to investigate the characteristics and degree of interrelatedness of groups of researchers (Bonaccorsi and Thoma, 2007; Cantner and Graf, 2006). Our research follows their lead and integrates social network analysis indicators of collaboration to the impact analysis.

Nanotechnology university scientists do not generally work in isolation but in increasingly large multidisciplinary research groups. Research funding is therefore rarely attributed to a single scientist, but much more commonly to a research team, especially when the amounts are rather large. The principle of collective invention, as proposed by Allen (1983), characterized by the free circulation of knowledge among socially connected agents, is very much a reality in this field. Lamoreaux and Sokoloff (1997), Dahl and Pedersen (2004), von Hippel (1987) and Schrader (1991) provide various examples of collective invention.

Theoretical simulation studies have shown that knowledge diffusion is more efficient through clustered networks (Cowan and Jonard, 2003), and relatively cliquish networks (Cowan and Jonard, 2004). The theoretical study of Cowan *et al.* (2004) shows that network structure significantly influences the long-term production of knowledge. Our paper examines these issues from an empirical point of view. In his empirical study, Newman (2001b) shows that the probability of a particular scientist acquiring new collaborators increases with the number of his past collaborators, and that the probability of a pair of scientists collaborating increases with the number of other collaborators they have in common (the creation of a clique). A number of scholars claim that collaboration persistency through time also positively influences knowledge productivity. For instance, Cowan *et al.* (2004) claim that previous collaborations increase the probability of a successful collaboration in the future. Furthermore, Fleming *et al.* (2006) argue that an inventor's past collaboration network will strongly influence subsequent productivity.

Proposition 3: Better-positioned scientists with the co-publication network are generally more productive.

Newman (2001a) observed that for most scientists, the path linking them to other scientists goes through a relatively small number of very central individuals. These central individuals generally receive the most research funding. The question therefore is whether the position and funding of these individuals influence their knowledge production. These are the issues that we wish to address in this paper.

3 Data and methodology

3.1 Data and variables

Canada does not escape the tendencies described in the previous section in terms of increased funding, publishing and patenting of nanotechnology research. According to Hu et al. (forthcoming), Canada occupies the 5th rank in 2005-2009 with 8% of the world nanotechnology publications, an improvement from the 11th rank for the 1998-2002 period (equivalent to 2% of the world's nanotechnology publications).

The latter corresponds to a period where nanotechnology public funding was considerably fragmented (Rosei, 2008). In the subsequent years, the Natural Sciences and Engineering Research Council of Canada (NSERC) launched the five-year 5M$ 'Nano Innovation Platform' which distributed its first research grants in 2003, while at the same time, the Canadian Institutes of Health Research (CIHR) invested roughly the same amount on regenerative medicine and nanomedicine. These initiatives obviously had an impact in raising the number of Canadian nanotechnology publications, but also of the number of patents (Dang et al., 2010), although the proportion of the world's patents that are attributed to Canada has dropped, mainly because of the rapid rise of China. It is probably too soon however to be able to really see the impact of this increased funding on patented innovation.

This research requires the integration of three data sources on funding, publishing and patenting: Elsevier's Scopus, the United States Patent and Trademark Office (USPTO) and the University Research Information System (*Système d'information sur la recherche universitaire* or *SIRU*) of the Quebec Ministry of Education, Leisure and Sports. Scopus provides the necessary data on nanotechnology scientific articles (date of publication, co-authors and their affiliations), while the USPTO provides the name and address of all inventors and patent assignees. SIRU contains the grants and contracts during the period 1985-2005 of all Quebec university scientists. The data for each scientist provides their affiliation as well as the yearly amount received from each grant or contract registered with the university[1].

[1] A number of Quebec scientists own small companies through which they perform consultative work. We have no means by which to estimate the breadth of such a practice but estimate it to be relatively small compared to the bulk of the funding received through the official channels, because of the very nature of nanotechnology research.

Using a keyword search similar to that of Porter *et al.* (2008), we have extracted all scientific articles and patents relating to nanotechnology for which at least one Canadian-affiliated scientist contributed for the period 1985-2005. This yields 4 883 patents that have been produced by 4 996 inventors and 23 250 articles authored by 24 083 scientists from which the co-publication networks will be characterized. Restricting the resulting sample to 1996-2005, because there has been a substantial change in the quality of Scopus before and after 1996, yields 17 803 articles. Merging the three databases required the careful examination of the surnames and first names (in SIRU) or initials (in Scopus and the USPTO) of scientists and their affiliations (or addresses) in all three databases. The intersection of the three databases results in the scientific production and financing of all Quebec nanotechnology academics. This exercise further reduces scientific output to 3 724 publications authored by 1 116 Quebec scientists and 566 patents involving 325 Quebec inventors. Finally, to ensure that these scientists are truly involved in nanotechnology, we select only those for which we can find at least 5 publications throughout the 21 years examined, hence eliminating the ‘occasional’ nanotechnology scientists. The resulting panel database contains 5 724 observations of 907 Quebec academics.

Using the social network analysis software Pajek, we then characterize the network of co-authors using co-publication links between scientists from the articles extracted. In these networks, the vertices are the co-authors or scientists and the edges between the vertices represent the co-authorship links of each article. In order to follow the evolution of collaboration over the years, we have created sub-networks using the co-publication links over periods of three and five years. An analysis of these sub-networks enabled us to describe their structural properties and to explore the collaborative behavior of nanotechnology scientists in Quebec.

An important consideration relates to the historical structure or time period of both the funding and collaboration measures. Public grants are generally awarded for a number of years. For example, Tier I Canada research chairs are generally awarded for periods of seven years (five years for Tier II chairs). Ordinary research grants vary from three to five years. Other major collaborative grants cover seven years of funding while smaller initiatives can be awarded for periods as short as one year. In the literature, the time period of collaborative networks vary from one study to the next. For instance, Schilling and Phelps (2007) use three-year windows for their firm collaborative networks. Gulati and Gargiulo (1999) prefer five-year windows and so does Stuart (2000). As a consequence, during the course of our analysis, three- and five-year sub-networks have been considered and the most robust results are reported in this paper, i.e., those for three-year sub-networks.

We seek to assess the direct impact of funding, i.e. the total amounts of grants and contracts on the number of articles published in a given year. Because of the reasons mentioned above, the average amount of funding over three and five years were included in our models and the three year averages were found to be the best suited to our data: [*AveGrant3*] and [*AveCont3*] represent respectively the average amount of grants and contracts received by an academic during the past three years. To distinguish between operating cost funds and those dedicated to infrastructure, we used the average amount of operating grants over three years [*AveGrantO3*] and the average amount of infrastructure grants over three years [*AveGrantI3*][2].

[2] Negligible amounts of contracts for infrastructure acquisition are present in the database. As consequence, we do not distinguish between the infrastructure contracts and operating cost contracts.

Our measures of network attributes focus on a scientist's position within the network: betweenness centrality and individual cliquishness. Betweenness centrality of a vertex (scientist) refers to the capacity of a scientist to link two other scientists from the same three-year sub-network through the smallest number of intermediaries [*Btwness3*]. If a greater proportion of the shortest paths between all other vertices 'goes through' a particular vertex, this vertex has a higher betweenness centrality and her role as an intermediary is more important. Cliquishness of a vertex is measured by the egocentric density of a vertex which is defined as the fraction of all pairs of the immediate neighbors of a vertex that are also directly connected to each other. The cliquishness of an individual in a three-year subnetwork [*Cliqness3*] basically measures the likelihood that two vertices that are connected to a specific third vertex are also connected to one another, hence forming a clique.

To investigate whether the relationship between patents and papers is one of reinforcement (or complementary, as Stephan et al., 2007 coined it) or of substitution (Klitkou and Gulbrandsen, 2010), we include the number of patents filed in the past three years [*nbPatent3*].

Furthermore, we add the time elapsed between the start of the nanotechnology activities of an academic in a given year to create a proxy for the nanotechnology 'career' age or experience of the researcher [*Age*]. This control variable accounts for the fact that generally, older scientists are more productive (Merton, 1973; Cole and Cole, 1973; Wray 2003 et 2004; Kyvik et Olsen, 2008). Other scholars however argue that the most extraordinary discoveries are made by researchers before their 40th birthday (Adams, 1946; Zuckerman, 1977; Stern, 1978; Gieryn, 1981).

Finally, to take into consideration university variations that would not otherwise be accounted for, we include university dummy variables [*dUniv*] for the Quebec universities: McGill University [*dUMcGill*], University of Montreal including Ecole Polytechnique of Montreal [*dUMontrealG*], Concordia University [*dUConcordia*], all the constituents of University of Quebec [*dUQG*], as well as University of Sherbrooke and Bishop University together as they are both located near Sherbrooke city [*dSherbrookeG*].

3.2 Model specification

As mentioned above, the goal of the project consists in determining whether researchers with a greater amount of grants or contracts and in better network positions generate more innovation in the form of scientific production. Our dependent variable is therefore the number of articles published in a given year [*nbArticle*]. Because the dependent variable is a count measure, we use negative binomial regressions specific to panel data to estimate the number of articles published by an individual in a given year. Appendix A provides details of the models used in this paper.

The model to be estimated can thus be expressed in reduced form as:

$$nbArticle_{it} = f\begin{pmatrix} AveGrant3_{it-1}, AveCont3_{it-1}, nbPatent3_{it-1}, \\ Btwness3_{t-2}, Cliqness3_{t-2}, Age_{it}, dUniv_i, dT_t \end{pmatrix} \qquad \text{Eq. (1)}$$

A problem then arises because the probability of obtaining grants depends on past publications, which also depend on the grants available prior to publication. Because of the high correlation between various lags of the same variables, this problem is apparent to that of simultaneity, which is a common cause of endogeneity. A second cause of endogeneity is related to unobserved heterogeneity, which in our case would be the intrinsic quality of the researchers. Despite our efforts to collect the most complete and accurate data to account for the majority of factors that contribute to explaining the variation in the number of publications, omitted variables (such as mobility of researchers between institutions) and measurement error are inevitably present in the data at our disposal. The most important source of endogeneity however, and the one for which we will try to correct, is simultaneity. In the absence of endogeneity, the negative binomial regression model presented in Eq. (1) would be sufficient. To correct the model for endogeneity, we use the Two-Stage Residual Inclusion (2SRI) method proposed by Terza et al. (2008).

The basic idea is to estimate the endogenous variable, in our case the average amount of grants received over three years [*AveGrant3*], with an ordinary least squares regression on a number of exogenous variables or instruments. The residue of this regression is then computed and used as an explanatory variable in the model of interest. Bíró (2009) uses this particular method with a negative binomial regression for the second stage regression. Details of the methodology are provided in Appendix A.

Although we have not yet found in the literature an application of the 2SRI model using panel data, we will estimate the 2SRI model considering the overall error term as equivalent to the error term of the model utilized by Terza et al. (2008). As robustness checks we will estimate non-panel 2SRI regressions, i.e. cross-section regressions with repeated measures to account for the non-independence of the same individual through time. We will therefore show the results corresponding to the 2SRI model with and without the panel data representation, taking into account the repeated measurements of individuals through time. The STATA procedure *xtnbreg* (second stage negative binomial regression) and *xtreg* (first stage OLS regression) will be used for the panel regressions, and the procedures *nbreg* (second stage negative binomial regression) and *reg* (first stage OLS regression) will be used with the *vce*(*cluster*) option to account for the non-independence of observations regarding the same individuals.

To correct for endogeneity, we include a number of variables that contribute to explaining the unobserved capabilities of a researcher to publish and his ability to raise public funds from grants. As grants are generally given on the basis of the past publication record of a scientist, the first instrument is the average yearly publication rate of each scientist in the three years prior to the grant [*AveArticle3*]. The second indicator is an ordered measure of the academic prestige linked to various research chairs. If an academic never had a chair in the period examined, the variable [*codeChair*] takes the value 0. If she has had an industrial chair at some point in her career, the variable takes the value 1, for NSERC or CIHR chairs, the variable takes the value 2, and finally, for Canada research chairs, the variable takes the value 3. Because we are interested in measuring the potential quality of academics, if an individual eventually reaches the top level of our chair classification, she will be attributed the top value for the entire period. Finally, the third attribute relates to the university to which an academic is affiliated. This accounts for the reputation of the establishment, the attraction power it has on different quality of individual researchers, and so on. This is accounted for by the average amount of grants raised by scientists per university in the past three years [*AveGrant3U*].

The regressions (first and second stages) to be estimated can therefore be expressed as:

$$AveGrant3_{it-1} = f\begin{pmatrix} AveArticle3_{it-2}, codeChair_i, AveGrant3U_{t-1}, AveCont3_{it-1}, \\ nbPatent3_{it-1}, Btwness3_{it-1}, Cliqness3_{it-1}, Age_{it}, dUniv_i, dT_t \end{pmatrix} \quad \text{Eq. (2)}$$

$$nbArticle_{it} = f\begin{pmatrix} AveGrant3_{it-1}, AveCont3_{it-1}, nbPatent3_{it-1}, Btwness3_{it-1}, \\ Cliqness3_{it-1}, Age_{it}, dUniv_i, dT_t, residual1st \end{pmatrix} \quad \text{Eq. (3)}$$

where Eq. (2) corresponds to Eq. (A.1) in appendix A and Eq. (2) corresponds to Eq. (A.2), and *residual1st* is the residual from Eq. (2). The model also includes year dummy variables [*dT*] to account for any yearly differences that would not be accounted for by the explanatory variables.

4 Descriptive statistics

Before turning to the regression results, let us first briefly describe some of the explanatory variables (which are further described in appendix B at the end of the paper). Fig. 1 presents the average number of articles per academic, our dependent variable, for each of the universities examined. McGill University generally dominates, followed by Laval University and the University of Montreal in second and third places. Concordia University rises sharply towards the end of the sample, despite a declining average amount of public funds received (Fig. 2).

Insert Fig. 1 approximately here

Insert Fig. 2 approximately here

Examining the average amount of research funds granted to individual researchers (Fig. 2) shows that until the turn of the century, the differences between the amounts received by scientists from different universities is not as pronounced as in the latter part of the sample. The peaks obtained by University of Montreal in 2000 and 2003, as well as by Laval University in 2002 and by McGill University in 2004 are mainly due to large infrastructure grants obtained by their scientists.

With the recruitment of new professors and the use of the Canadian Foundation for Innovation (CFI), these universities have built a considerable research infrastructure. The recent increase in scientific production (though not apparent from the graphs which show averages per scientist) is probably attributable to this investment. Scientists from Concordia, Sherbrooke and Quebec universities receive less funds per year than their colleagues of McGill, Montreal and Laval universities. Fig. 3 indicates that researchers from the University of Montreal have on average received almost double the industrial contracts of McGill University. This would tend to suggest more applied work for/with industry. In that game, Laval University wins hands down with the highest proportion of contracts among all Quebec universities.

Turning now to the network measures, we find that both betweenness centrality and cliquishness have decreased slightly over the years (see Fig. 4) but that the former has stabilized since the turn of the century. As more scientists from a number of different disciplines turn their attention to nanotechnology, it is to be expected that the betweenness centrality of individuals will decrease over time. This phenomenon is also observed for nanotechnology patents over the same period by Beaudry and Schiffauerova (2011). The authors link this diminution over time to the increased fragmentation of the field due to its development in a vast array of domains of application.

Insert Fig. 4 approximately here

Because we used the variable [*Age*] as is a proxy for the experience gained in nanotechnology by the researcher over time, we examine the interaction of this variable with the number of articles and the number of patents (Fig. 5). As mentioned by Lee and Bozeman (2005) and Lehman (1953), research productivity grows with the age of the scientist and peaks at a certain period. The latter vary with the discipline and whether the research is fundamental or more technology-oriented. In our case, the age of the scientific production continues to increase with age, while patenting tends to follow an inverted U-shaped curve. Both curves imply non-linear effects, which will be taken into consideration in the regressions that follow.

Insert Fig. 5 approximately here

5 Results

The regressions estimate the factors that influence researcher productivity measured by the number of articles (the results are shown in Table 1). Our analysis has considered a lag structure of one-, two- and three-year lags for most variables of the model, similar to what Schilling and Phelps (2007) have used in their model. We have tested all combinations of lags and the most robust results combine one- and two-year lags (one-year lag was found to be most appropriate for public grants and contracts while two-year lags were more robust for the network variables). We also included interaction effects between variables, and a quadratic term for others to account for non-linear effects.

Table 1 presents the results of 10 regression models, using a number of variables to represent grants, contracts and network position indicators. The first two models do not consider the endogeneity; they estimate Eq. (1). Model (1) uses a panel data negative binomial regression model while model (2) estimates a cross-section negative binomial model (i.e. without the panel data representation) using a clustering method to include repeated observations of the same scientist over the years. Models (3) to (8) are the second stage regressions, Eq. (3), of the 2SRI method with a panel data negative binomial regression. We tested different sets of variables over a hierarchical progression for the inclusion of the variables. The last two models, (9) and (10), estimate the second stage regression of the 2SRI cross-section negative binomial model (without the panel data structure) using the same clustering method. Table C.1 in the appendix presents the related results for the first stage regressions, Eq. (2), of the 2SRI models.

Insert Table 1 approximately here

Insert Table 2 approximately here

Let us now take each variable in turn and analyze its influence on scientific production. First, the influence of the average amount of grants over three years [*AveGrant3*] on the number of articles published follows a quadratic convex function (J-shaped), which implies that the productivity of the researcher increases exponentially (the linear effect is not significantly different from 0). This indicates that larger grants, or more funding, increase the number of published articles, a result in accordance with Arora et al. (1998) and Zucker et al. (1997). The results are similar if we distinguish operating cost grants [*AveGrantO3*] and infrastructure grants [*AveGrantI3*] in Table 2. This last variable only appears in the first stage regression as it is not correlated with the number of articles, nor was it significant in the second stage regression (this contrasts with Payne and Siow, 2003 who find a direct effect of infrastructure grants on scientific output). The average amount of infrastructure grants is therefore added as an instrument in the first stage regressions and contributes to explaining the average amount of operating cost grants received by an academic. Its influence on the amount of operating cost grants vary linearly (see Table C.2 in the appendix). As with the average amount of public funds, the average amount of operating cost grants raised by a scientist has a positive effect on the productivity of the researcher. Operating cost grants are destined for the direct resources working on the research (students, laboratory assistant, research assistant, equipment maintenance, etc.), which are important for the discovery of any knowledge worth publishing. Through the different models, we can say that the simple (linear) effect of the total amount is positive and significant, but that its effect is closer to exponential as shown by the coefficient of the quadratic effect introduced.

Turning now to our instruments to correct for potential endogeneity of the average amount of grants received, in Eq. (2), we generally find them to have a positive and significant effect. These results are presented in Table C.1 in the appendix (Table C.2 presents the corresponding results for the distinction between operating cost and infrastructure grants). A greater yearly average of publications in the past three years has the expected positive influence on the likelihood of raising more public research funds, and so does the chair ‘prestige’ status. These findings obviously follow the general intuition and more specifically support those of Arora et al. (1998). The average amount of research funds raised by other university colleagues of the same institution also contributes to explaining our endogenous variable. In these regressions, we also find that researchers that raise more funds from private contracts also raise more funds from public sources.

Generally, private funds are destined for specific projects in relation to an industrial problem. This work is considered ‘protected’ for the industry as it may contain confidential content. That’s why companies set restrictions for the research results that would most of the time prevent a scientist from publishing articles related to the output of his industry collaboration. The output of privately funded research tends to appear more as patents, because it guarantees ownership of the intellectual property to the investors. The total amount of contracts does not however appear to have a significant effect (neither negative, nor positive) on the number of publications, only in one of the cross-section (regression 9) is it negative and significant. This finding contradicts the literature that suggests a reinforcing effect of private funds on research productivity (Gulbrandsen and Smeby, 2005; Van Looy et al., 2004), and the literature suggesting a substitution effect (anticipated for instance by Welsh et al., 2008 and Blumenthal et al., 1996). Our findings may be explained by the fact that nanotechnology is still relatively far from the market. Because the field is quite young, private contracts may result in scientific articles, but they may also yield patents in the fields closer to technology applications (the evolution from microelectronics to nanoelectronics for example).

For this reason, we have tested whether there was a moderating effect between patents and private contracts, but to no avail, the resulting interactive variable was never significant. Although we find no evidence of impact on scientific production, the very nature of nanotechnology calls for this closeness between industry and universities. Canada has invested vast amounts on infrastructure and laboratory equipment, mostly from public sources. These expensive resources (both in infrastructure and in the skilled labor necessary for its operation) would be difficult to finance privately and hence contribute to attracting industries (Robinson et al., 2007 for instance examine cluster formation enabled by these infrastructures or platforms). The interaction between publicly funded research infrastructure and private contracts is therefore important to examine.

Both variables [*AveGrantI3* and *AveCont3*] in Table C.1 and Table C.2 have a positive and significant influence on the average amount of public grants raised by a scientist. In fact, having the laboratory machinery and the equipment necessary for high technology research is a strong argument to attract the grants to operate them. Similarly, the average amount of contract seems to attract more operating cost funds to a researcher. The positive and significant effect of the contract variable suggests a Matthew effect (money attracts more money) that is very much verified in our data set (Merton, 1968). Arora et al. (1998), suggest that funding is more likely to be directed towards scientists with an established tracked record of successes, and we would add a tracked record that was the result of more funding. The interaction between the two variables, however, has a negative and significant effect, implying that the infrastructure used in conjunction with private firms reduces the need to obtain public funding. In regards to the use of infrastructure, public and private funds therefore appear to be substitutes.

Industrial interests or potential commercialization does nevertheless have an influence as the number of patents has an inverted-U relationship with the number of articles. The maximum of the resulting curve corresponds roughly to 30 patents over three years. As a consequence, before that point, the first patents tend to reinforce an individual's scientific production and strengthen the reputation of the researcher. Beyond that point, however, contributing to more patents implies a declining number of articles published, *ceteris paribus*. Hence patents are detrimental to scientific productivity only beyond a relatively large amount of patent applications filed over a period of three years. Once a rather large number of patent applications have been made, scientists tend to prioritize applied work and focus on patenting; it clearly becomes a career choice, which may then be more profitable.

Regarding the influence of collaboration, we find that betweenness centrality [*Btwness3*] has a positive and significant effect on the number of articles. This confirms our expectation that a researcher with a more central position in the co-publication network, i.e. a more influential intermediary, generally publishes more articles. In addition, past individual cliquishness [*cliqness3*] tends to have a negative effect on scientific productivity. Once we account for nonlinearities of this variable, we find what appears like the left-hand branch of an inverted-U relationship with the number of published articles, i.e. scientific productivity exhibits diminishing returns to increased cliquishness. A higher cliquishness value implies that the collaborators of an academic are more likely to be collaborators as well, i.e. to form a clique. Our results would tend to suggest that if a researcher maintains some degree of segregation between the groups with whom he collaborates, which would yield a lower cliquishness value, his probability of publishing is greater if his ‘clique’ is slightly more integrated. Further along the curve of increased cliquishness, however, the returns of a greater integration of the clique are much smaller. In some fields, large multidisciplinary teams are necessary and, as a consequence of the integration of knowledge from various sources, publication is slightly slower as various disciplines adjust to each other. When a field is in its infancy, as nanotechnology clearly is, the skills and knowledge necessary for research probably go beyond the restricted circle of a scientist’s direct collaborators, especially when the resulting technology has a vast array of potential applications. This would explain, to some extent, why working in increasingly cliquish nanotechnology networks do not tend to augment the productivity of each scientist as much as when there is a rather fragmented clique around a scientist. This would tend to support an extension to scientific productivity of Cowan and Jonard’s (2004) argument that knowledge diffusion is more efficient in ‘relatively’ cliquish networks, i.e. not too cliquish but cliquish enough.

Examining closely regressions (3), (4) and (5) shows that betweenness centrality interacts with other variables in our models and moderates their influence on the dependent variable, particularly patenting and cliquishness. To counter this intrinsic relation of betweenness centrality with these variables, we have introduced interactive variables with cliquishness, the average amount of contracts and the number of patents[3]. Interacting betweenness centrality with cliquishness decreases the diminishing returns impact of the latter. In contrast, interacting

[3] Other interactions have been tested, but were non significant. Only those presented in Table 1 are significant and are worth including in the models.

betweenness centrality with the total number of patents over three years contributes to dampening the inverted-U shaped effect of patenting on scientific productivity.

Our last explanatory variable, the nanotechnology ‘career’ age of a scientist, generally has a positive effect on scientific productivity, in line with Fig. 5. When we add a quadratic term, the curvature of the relationship appears. Around 16 years after starting nanotechnology work, scientific production starts to decline. It would therefore appear that it is the mid-career scientists that have the highest scientific production, a result in line with that of Cole (1979), Wray (2003 and 2004) as well as Kyvik and Olsen (2008).

A recent debate (Wells, 2009) on university research funding in Canada saw the ‘big 5’ universities (University of British Columbia, University of Alberta, University of Toronto, University of Montreal and McGill University) argue that they should receive all (or the bulk of) the research funding, concentrate only on graduate training and leave undergraduate teaching to the other Canadian universities. The argument put forward in Wells’ (2009) article by the five top university presidents is that they should be allowed to “pursue world-class scientific research and train the most capable graduate students”.

Although this proposal raised a wall of protestation in Canada, the question as to where does research funding yields the highest scientific productivity deserves an answer. In this article, we focus on the Quebec universities and compare the publication results obtained by two of the ‘big 5’ (University of Montreal and McGill University) as a result of the research funding received. From the analysis of the university dummy variables included in the regressions, we cannot say that our results support their claim, certainly not in terms of scientific production. The omitted dummy variable is for McGill University, to which the results should be compared. All university dummy variables are significantly different from McGill University with the exception of Concordia University, which is sometimes weakly significant. In the field of nanotechnology, the University of Montreal does not appear to deserve its ‘title’: Being located at the University of Montreal has no significantly different effect than being located at Laval University (in Quebec city). We can say that there is no evidence so far that researchers from the two ‘best’ universities in Quebec publish ‘more’ than their colleagues in other universities in the province. The ‘publish or perish game’ is similar for all universities and researchers conform to it.

6 Discussion and conclusion

At the beginning of this paper, we set out to investigate whether the funding and organization (read collaboration or co-authorship) of research has an impact on the output from this research. To that effect, we suggested three propositions, two on funding and one on the individual network position of an academic.

To the first part of the question, on the funding, the answer is overwhelmingly ‘yes there is an impact’, but there are subtleties. While more public research funds undoubtedly lead to more scientific articles, hence supporting proposition 1 and the work of other scholars (for instance Arora et al., 1998, Zucker et al. 2007), the relationship between private funds and scientific production is inexistent (in contrast with Van Looy et al., 2004), hence rejecting proposition 2. Contracts, which are generally associated with more applied research, do not have the commonly found reinforcing impact on the scientific production in nanotechnology. Public policy should not therefore consider industrial contracting as a threat to the creation of a collective knowledge base, not at the current level of industry involvement in any case.

Since the amount of private research funds at the disposal of researchers does not yield a convincing story, the number of patents to which a researcher has contributed may play a more fundamental role. We indeed find that it is not so much the fact that academics collaborate with firms that affects their publishing record, it is too much patenting. And when we mean too much, we imply more than 20 to 40 patents over a period of three years, which clearly is a career choice. Below that extraordinary contribution to technology, we clearly find a reinforcement effect between patenting and publishing, hence supporting the findings of a number of scholars (Breschi et al., 2005; Calderini and Franzoni, 2004; Calderini et al., 2007; Meyer, 2006; Van Looy et al., 2006). The implication in terms of public policy would be to encourage, or at least not discourage, scientists to bring their research closer to the market as the protection of intellectual property does have a positive impact on their scientific production when performed within reasonable bounds, bearing in mind that too much of a good thing can be detrimental to scientific production.

In a field such as nanotechnology, where innovation increasingly requires multidisciplinary teams, innovating alone is no longer possible. The most 'important' scientists should thus occupy the most central positions within the co-authorship networks. Betweenness centrality acts as a proxy for a researcher' importance as an intermediary in our impact regressions. We show that better intermediaries have a better scientific performance. In addition, the structure of research teams, measured by the cliquishness, or clustering coefficient, also has an influence on scientific output. The maximum cliquishness, however, does not bring as much productivity benefits as we would expect, the relationship between cliquishness and scientific production exhibiting diminishing returns. In other words, one's efforts in integrating team members into a more cliquish network may not be fully rewarded. Some level of fragmentation in the immediate surrounding network of a scientist is therefore acceptable. To our knowledge, this is quite a novel result which raises some interesting questions regarding the optimal size and diversity of teams, compared with the amount of effort, expense and coordination that is required for the management of such teams. For a number of years now, Canada has promoted networking and multidiciplinarity via its granting councils, it is now time to pause and to measure the impacts of such policies in terms of scientific output and technology as excessive networking may not be as beneficial as one would have thought.

There are a number of limitations to our research. First, we have examined a rather narrow field, nanotechnology. In order to fully support the claims of two of the 'big 5' universities in Quebec, for instance, one would have to assess all the disciplines in which both universities specialize. A second limitation concerns the mobility of scientists. Once a scientist moves out of the province, he disappears from our funding radar even though he may remain active. A third limitation of our study is the data. Although we have tried to extract as much of the articles of the researchers identified in the nanotechnology fields, it is possible that some escaped our net. Scopus does not include all scientific journals and as more journals are added every year, the coverage changes constantly, adding a time bias to the analysis. A fourth limitation stems from the fact that our model cannot measure the impact of graduate students on the production of a research group, because they are not academic professors employed at a university, they appear to have no funding. Finally, we have not yet been able to explicitly take into account research teams apart from those measured by co-publications.

This last limitation exemplifies an important knowledge gap on research teams. and raises a number of interesting questions regarding the organization of research between localized and delocalized teams, and how public funding contributes to the constitution of these teams, especially in light of the new ‘networking’ policies. Is more knowledge generated as a consequence of these policies? Similarly, we need a more comprehensive examination of whether private funding and the interaction with industry modify the composition of these research teams. Thursby and Thursby (2011), for instance, have made an interesting contribution regarding various interactions with industry and their impact. In other words, we need to evaluate whether the changes imposed on researchers by grant awarding bodies are a step in the right direction.

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Appendix A – Model specifications

Our dependent variable [*nbArticle*] being a count measure for each individual scientist over the years, a Poisson regression is generally appropriate for this purpose (Hausman *et al*., 1984)

$$\Pr\left(Y_{it}=y_{it}\right)=\exp\lambda\left(x_{it}\right)\cdot\left[\frac{\lambda\left(x_{it}\right)}{y_{it}!}\right].$$

The model expresses the probability of the number of occurrence of the observed value y_{it}, i.e. the number of articles, depending on the parameter λ that is a function of the explanatory variables x_{it}. This model implies the strong assumption that the variance of the number of occurrences is equal to the expected number of occurrences $Var\left[Y_{it}\right]=E\left[Y_{it}\right]$. This assumption further implies that there is no over-dispersion (when the variance exceeds the mean) in the sample. This over-dispersion causes for the standard errors to be underestimated, and hence for the significance of the coefficients to be overestimated. The negative binomial model is a solution to this over-dispersion, in which the parameter λ is expressed as $\lambda=\exp\left(\pi x_{it}\right)\varepsilon$, where the error ε follows a Gamma distribution. This leads to write the variance as $Var\left[Y_{it}\right]=E\left[Y_{it}\right]\left(1+\alpha E\left[Y_{it}\right]\right)$, where α is the parameter of the Gamma distribution.

In order to account for endogeneity within the negative binomial regression model, we use the Two-Stage Residual Inclusion (2SRI) method proposed by Terza et al. (2008). The main assumption of the model is that the conditional mean of the dependent variable can be written as (from Terza et al., 2008) $E\left[y_i\middle|x_{in},x_{ix},x_{iu}\right]=M\left(x_{in}\beta_n+x_{ix}\beta_x+x_{iu}\beta_u\right)$, where $M\left(\cdot\right)$ is a non linear function, x_{in} is a vector of endogenous variables (in our case, there is only one), x_{ix} is a vector of exogenous variables, and x_{iu} is a vector of unobservable latent variables (omitted variables) that has an effect on the dependent variable and is correlated with the endogenous variable. The corresponding regression model can be written as $y_i = M\left(x_{in}\beta_n + x_{ix}\beta_x + x_{iu}\beta_u\right) + u_i$, where u_i is the error term.

The first regression (called auxiliary regression) therefore consists in modelling the relationship between the endogenous variable and the unobserved latent variables using a set of instrumental variables (IV), w_i , that can be written as follows (in this case, we consider a linear relationship):

$$x_{in} = w_i\alpha + x_{iu} \qquad \text{Eq. (A.1)}$$

where $w_i = \left[x_{in}\ w^+\right]$ and w^+ is the vector of instrumental variables and α is the vector of parameters. These variable have to meet the three following conditions: first, the instrumental variables must not be correlated with the unobserved variables $E\left[x_u | w_i\right] = 0$; second, the instrumental variables must be sufficiently correlated with the endogenous variable, which means that the instrumental variables would be sufficient to estimate the endogenous variable; and third, they are not correlated with the main variable of interest, nor with the error term.

The first stage consists in estimating the auxiliary regression by ordinary least squares (OLS) and calculating the predicted values, $\hat{x}_{in} = w_i\hat{\alpha}$, where $\hat{\alpha}$ is the estimate of α for the first equation (auxiliary regression). Subsequently, the residuals of the unobserved variables are calculated by $x_{iu} = x_{in} - \hat{x}_{in}$.

The second stage then consists in estimating the negative binomial regression model by introducing the residues as an explanatory variable. In the case of panel data, the error term contains both u_i and a time related error component e_{it}.

$$y_{it} = M\left(x_{\text{int}}\beta_n + x_{ixt}\beta_x + x_{iut}\beta_u\right) + u_i + e_{it} \qquad \text{Eq. (A.2)}$$

Appendix B – Descriptive statistics

Insert Table B.1 approximately here

Insert Table B.2 approximately here

Appendix C – Additional regression results

Insert Table C.1 approximately here

Insert Table C.2 approximately here

Figure

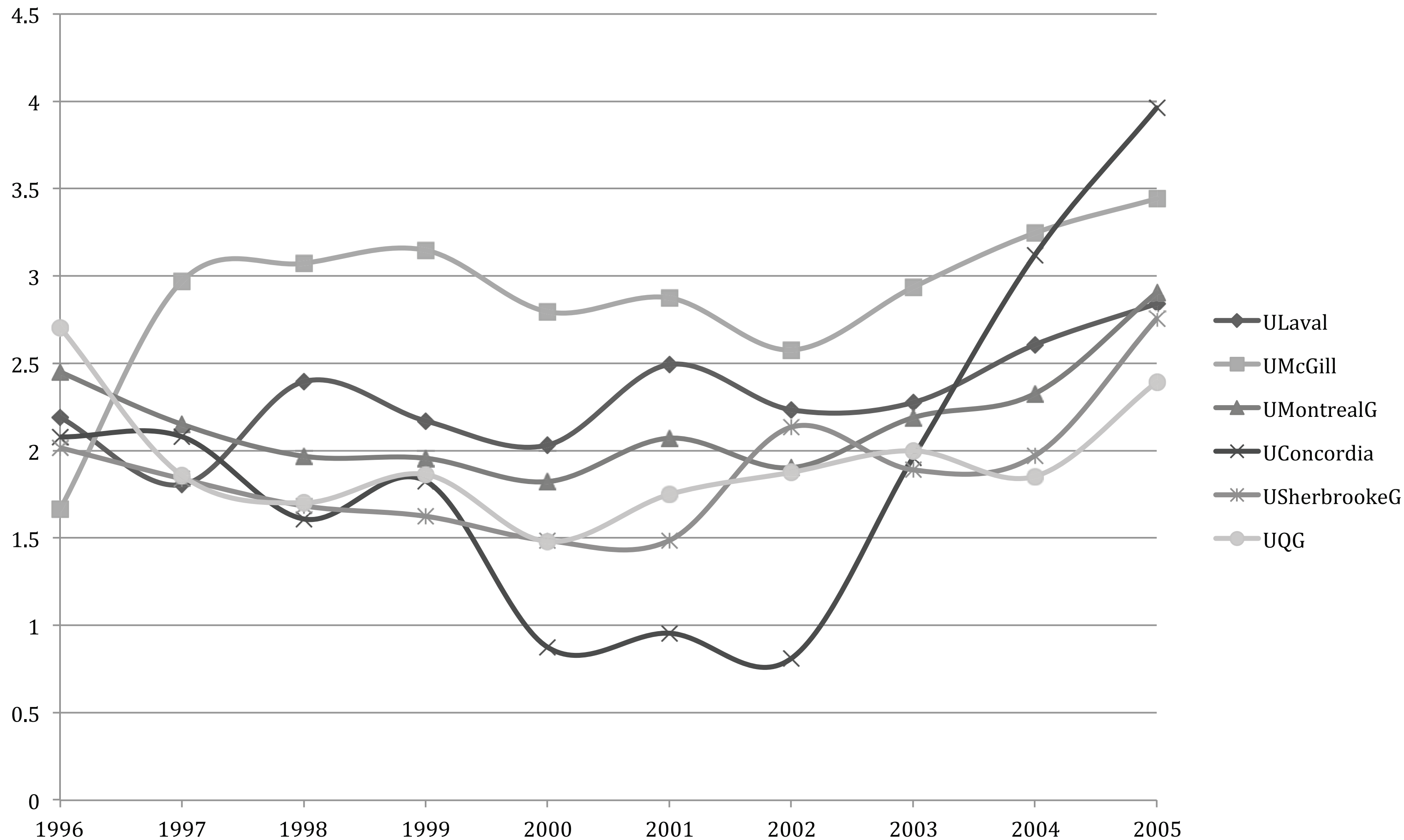

Fig. 1 – Average number of articles per academic published per year

Figure

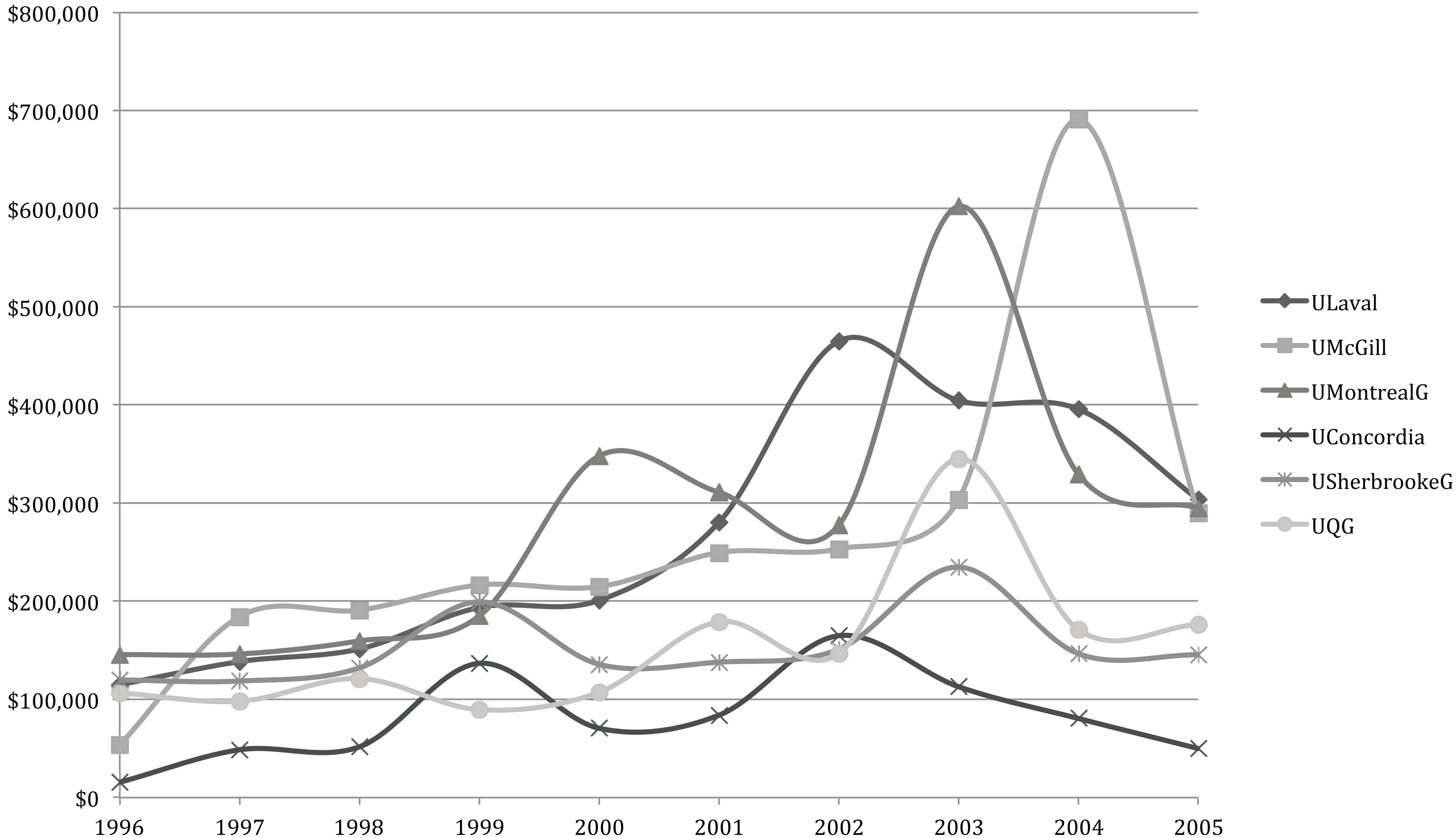

Fig. 2 – Average amount of public funds received per academic (in constant Canadian dollars of 2002) per year

Figure

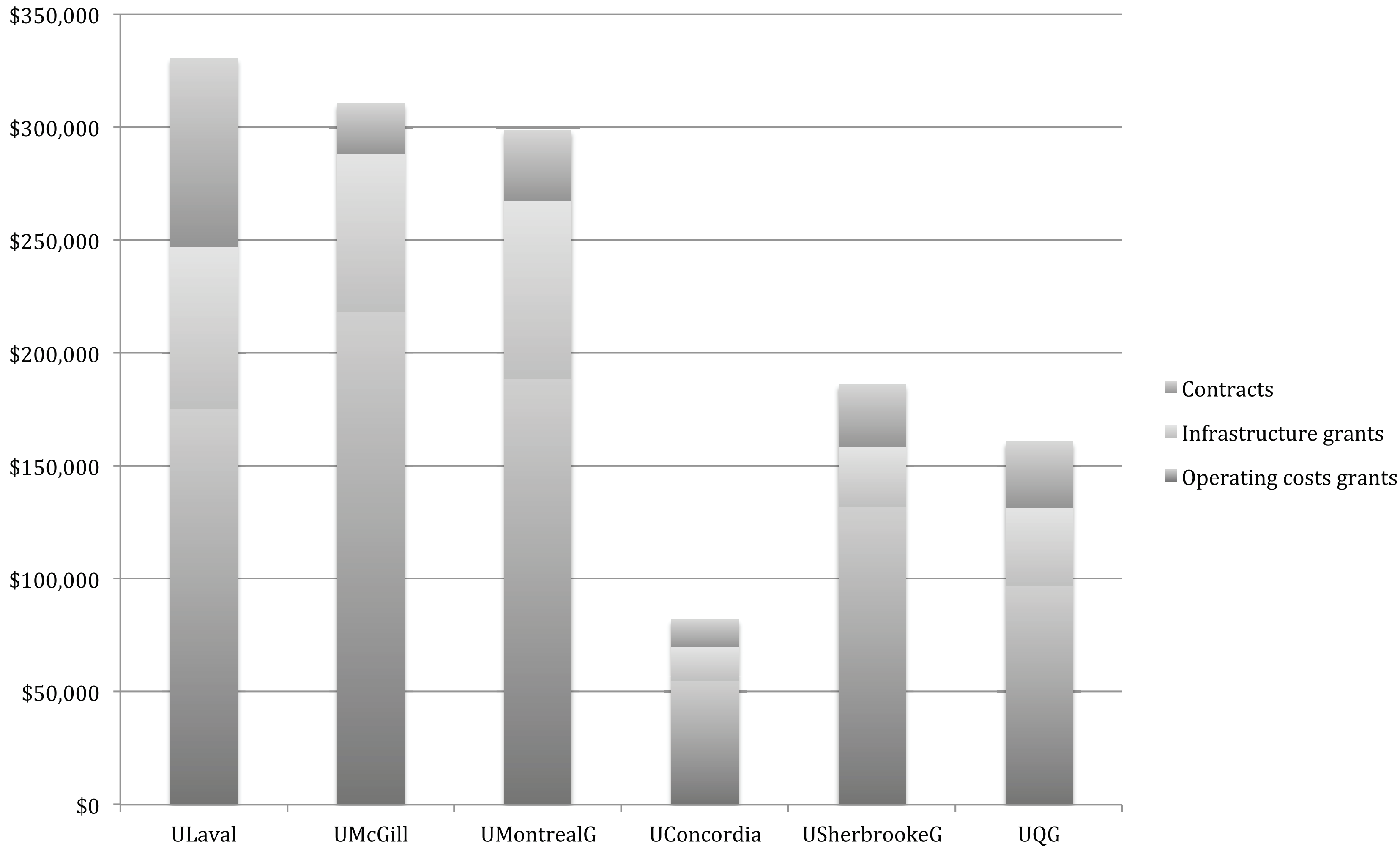

Fig. 3 – Average amount of public (operating costs grants and infrastructure grants) and private (contracts) funds received (in constant Canadian dollars of 2002) per scientist for the period 1996-2005

Figure

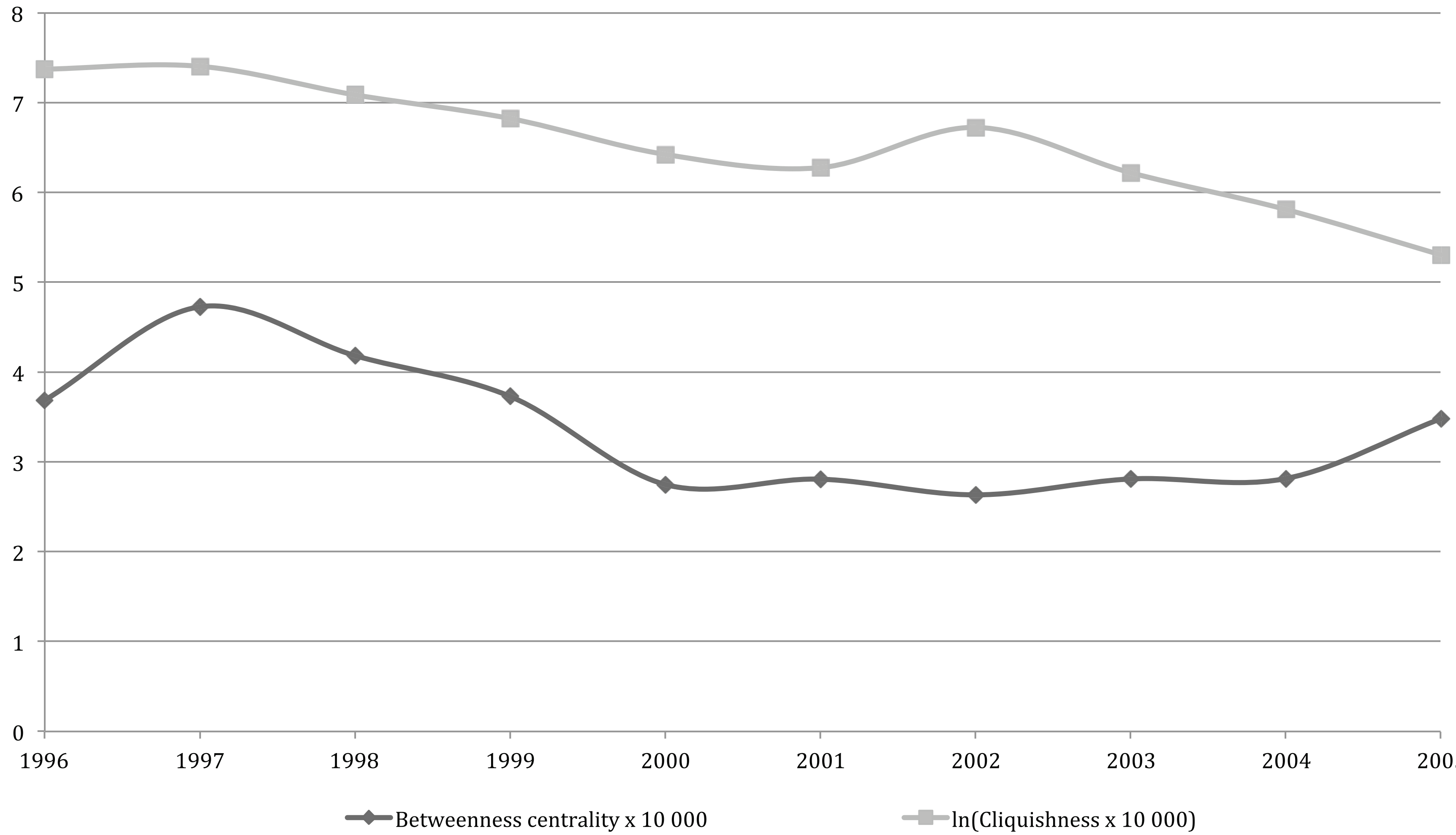

Fig. 4 – Average betweenness centrality (*Btwness3* x 10^4) and cliquishness (*Cliqness3* x 10^4) per year

Figure

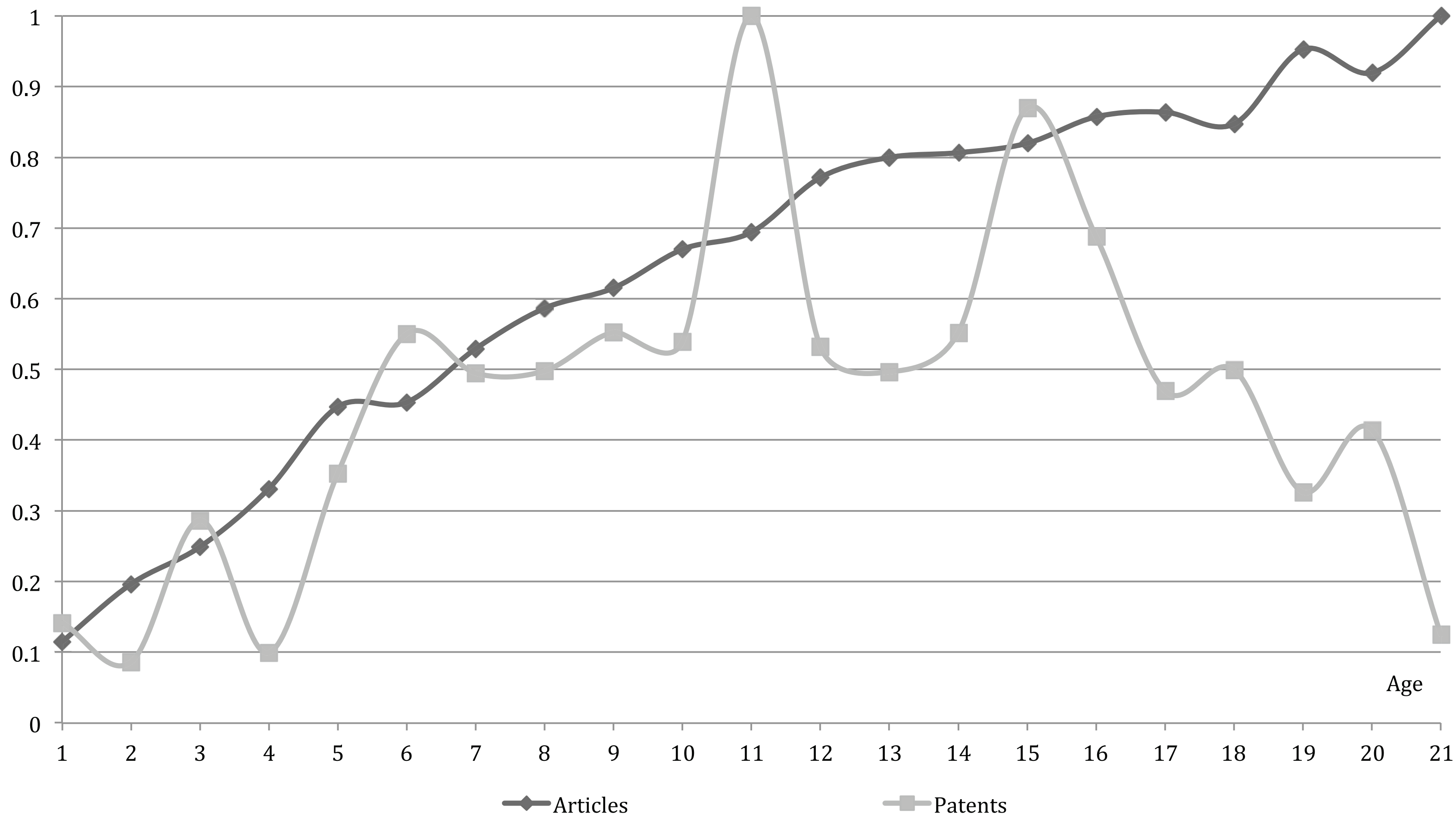

Fig. 5 – Index (relative to the maximum value over the years) of the number of articles and patents by the nanotechnology 'career' age of scientists

Table

Table 1 – Negative binomial regression results – number of articles per academic per year

Model	**Panel**	**X-section**	**Panel Two-Stage Residual Inclusion (2SRI)**						**X-section 2SRI**	
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Average amount of grants over the past 3 years										
ln($AveGrant3_{t-1}$)	-0.0628 ***	-0.0877 ***	0.0458 ***	0.0498 ***	0.0438 ***	-0.0201	-0.0322	-0.0302	0.2257 ***	0.1331 ***
	(0.0141)	(0.0189)	(0.0183)	(0.0180)	(0.0180)	(0.0252)	(0.0251)	(0.0251)	(0.0339)	(0.0386)
[ln($AveGrant3_{t-1}$)]^2	0.0052 ***	0.0081 ***				0.0049 ***	0.0049 ***	0.0048 ***		0.0058 ***
	(0.0011)	(0.0016)				(0.0011)	(0.0011)	(0.0011)		(0.0015)
Average amount of contracts over the past 3 years										
ln($AveCont3_{t-1}$)	-0.0100	-0.0047	0.0038	0.0046	0.0053	-0.0112	-0.0110	-0.0135	-0.0137 ***	-0.0251
	(0.0136)	(0.0188)	(0.0035)	(0.0035)	(0.0036)	(0.0137)	(0.0136)	(0.0137)	(0.0057)	(0.0182)
[ln($AveCont3_{t-1}$)]^2	0.0015	0.0010				0.0013	0.0016	0.0016		0.0008
	(0.0013)	(0.0018)				(0.0013)	(0.0013)	(0.0013)		(0.0017)
Number of patent applications of the past 3 years										
$nbPatent3_{t-1}$	0.0777 ***	0.0902 ***	0.0177 ***	-0.0034	0.0500 ***	0.0669 ***	0.0579 ***	0.0800 ***	0.0518 ***	0.0960 ***
	(0.0136)	(0.0210)	(0.0044)	(0.0049)	(0.0084)	(0.0110)	(0.0116)	(0.0136)	(0.0132)	(0.0194)
[$nbPatent3_{t-1}$]^2	-0.0012 **	-0.0020 **				-0.0015 ***	-0.0006	-0.0013 **		-0.0023 ***
	(0.0005)	(0.0008)				(0.0002)	(0.0005)	(0.0005)		(0.0007)
3-year network betweenness centrality										
$Btwness3_{t-2}$ x10^4	0.0426 ***	0.1238 ***		0.0101 ***	0.0395 ***	0.0111 ***	0.0412 ***	0.0414 ***	0.0871 ***	0.0993 ***
	(0.0067)	(0.01474)		(0.0011)	(0.0067)	(0.0011)	(0.0068)	(0.0067)	(0.0180)	(0.0147)
3-year network cliquishness										
ln($Cliqness3_{t-2}$x10^4)	0.0687 **	0.2075 ***	-0.0045 *	-0.0049 **	-0.0043 *	0.0479	0.0764 **	0.0701 **	-0.0207 ***	0.2360 ***
	(0.0309)	(0.0450)	(0.0025)	(0.0025)	(0.0025)	(0.0300)	(0.0309)	(0.0309)	(0.0024)	(0.0438)
[ln($Cliqness3_{t-2}$x10^4)]^2	-0.0025 **	-0.0075 ***				-0.0018 *	-0.0027 ***	-0.0025 **		-0.0084 ***
	(0.0010)	(0.0015)				(0.0010)	(0.0010)	(0.0010)		(0.0015)
Nanotechnology 'career' age of an academic										
Age_t	0.0895 ***	0.0504 **	0.0312 ***	0.0243 ***	0.0204 **	0.0689 ***	0.0724 ***	0.0710 ***	-0.0207 ***	-0.0277
	(0.0160)	(0.0184)	(0.0071)	(0.0068)	(0.0066)	(0.0198)	(0.0198)	(0.0197)	(0.0074)	(0.0230)
Age_t^2	-0.0027 ***	-0.0018 **				-0.0020 ***	-0.0022 ***	-0.0021 ***		0.0002
	(0.0006)	(0.0007)				(0.0007)	(0.0007)	(0.0007)		(0.0008)
Interaction variables										
($Btwness3_{t-2}$ x10^4) x	-0.0048 ***	-0.0155 ***			-0.0042 ***		-0.0046 ***	-0.0042 ***	-0.0086 **	-0.0113 ***
ln($Cliqness3_{t-2}$)	(0.0010)	(0.0024)			(0.0010)		(0.0011)	(0.0011)	(0.0031)	(0.0025)
($Btwness3_{t-2}$ x10^4) x	0.0002	0.0009 **			-0.0001		-0.0002	0.0001	0.0004	0.0006
ln($AveCont3_{t-1}$)	(0.0002)	(0.0004)			(0.0001)		(0.0002)	(0.0002)	(0.0006)	(0.0004)
($Btwness3_{t-2}$ x10^4) x	-0.0017 ***	-0.0036 ***			-0.0005 ***		-0.0002	-0.0018 ***	-0.0009 ***	-0.0039 ***
$nbPatent3_{t-1}$	(0.0005)	(0.0007)			(0.0001)		(0.0001)	(0.0005)	(0.0001)	(0.0007)

Model	**Panel**	**X-section**			**Panel Two-Stage Residual Inclusion (2SRI)**				**X-section 2SRI**	
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
($Btwness3_{t-2}$ x10^4) x	2.6E-05 ***	6.0E-05 ***						2.8E-05 ***		6.4E-05 ***
[$nbPatent3_{t-1}$]^2	(0.9E-05)	(1.3E-05)						(0.9E-05)		(1.3E-05)
Universities dummy variables [a]										
dULaval	-0.2159 ***	-0.0831 *	-0.3256 ***	-0.2949 ***	-0.2565 ***	-0.2707 ***	-0.2391 ***	-0.2359 ***	-0.2441 ***	-0.2130 ***
	(0.0633)	(0.0578)	(0.0729)	(0.0682)	(0.0658)	(0.0659)	(0.6046)	(0.0642)	(0.0621)	(0.0586)
dUMontrealG	-0.2370 ***	-0.1055 **	-0.3458 ***	-0.2922 ***	-0.2653 ***	-0.2798 ***	-0.2488 ***	-0.2491 ***	-0.2269 ***	-0.2091 ***
	(0.0599)	(0.0542)	(0.0677)	(0.0637)	(0.0615)	(0.0616)	(0.0604)	(0.0601)	(0.0578)	(0.0547)
dUConcordia	-0.1412 **	-0.1482 *	-0.0831	-0.1561	-0.1301	-0.1372	-0.1086	-0.1113	-0.0101	-0.0247
	(0.1198)	(0.1340)	(0.1401)	(0.1294)	(0.1241)	(0.1254)	(0.1218)	(0.1214)	(0.1269)	(0.1329)
dUSherbrookeG	-0.3182 ***	-0.1656 ***	-0.4686 ***	-0.4077 ***	-0.3626 ***	-0.3579 ***	-0.3225 ***	-0.3224 ***	-0.2947 ***	-0.2391 ***
	(0.0831)	(0.0702)	(0.0934)	(0.0880)	(0.0849)	(0.0855)	(0.0836)	(0.0833)	(0.0742)	(0.0725)
dUQuebecG	-0.3288 ***	-0.1538 **	-0.4452 ***	-0.3854 ***	-0.3505 ***	-0.3486 ***	-0.3207 ***	-0.3197 ***	-0.1571 **	-0.1227 *
	(0.0728)	(0.0749)	(0.0816)	(0.0768)	(0.0740)	(0.0748)	(0.0732)	(0.0729)	(0.0715)	(0.0676)
Residuals from 1st stage			-0.0472 **	-0.0516 ***	-0.0448 **	-0.0412 **	-0.0287	-0.0302	-0.2202 ***	-0.2017 ***
			(0.0190)	(0.0186)	(0.0186)	(0.0192)	(0.0193)	(0.0193)	(0.0346)	(0.0322)
Constant	1.3496 ***	-0.2356 **	1.7311 ***	1.6179 ***	1.6283 ***	1.3036 ***	1.1949 ***	1.2101 ***	-0.8956 ***	-1.6558 ***
	(0.1946)	(0.2295)	(0.1733)	(0.1709)	(0.1694)	(0.2137)	(0.2151)	(0.2148)	(0.2809)	(0.3344)
Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ln(r)	2.6894 ***		2.3980 ***	2.5312 ***	2.6269 ***	2.6322 ***	2.6837 ***	2.6977 ***		
	(0.0837)		(0.0796)	(0.0812)	(0.0824)	(0.0830)	(0.0837)	(0.0840)		
ln(s)	1.5361 ***		1.1760 ***	1.3565 ***	1.4713 ***	1.4539 ***	1.5327 ***	1.5466 ***		
	(0.0799)		(0.0660)	(0.0725)	(0.0766)	(0.0764)	(0.0800)	(0.0805)		
ln(alpha)		-0.9424 ***							-0.9329 ***	-1.0043 ***
		(0.0563)							(0.0521)	(0.0536)
Nb observations	5739	5739	5724	5724	5724	5724	5724	5724	5724	5724
Nb academics	907	907	907	907	907	907	907	907	907	907
Average nb years	6.33	6.33	6.31	6.31	6.31	6.31	6.31	6.31	6.31	6.31
Log likelihood	-11011.2	-11403.2	-11679.5	-11040.6	-11006.8	-10994.9	-10983.3	-10978.3	-11384.3	-11314.1
Wald χ^2	448.85 ***	4985.98 ***	212.25 ***	309.50 ***	390.95 ***	411.84 ***	441.42 ***	455.20 ***	739.13 ***	5651.01 ***

Notes: ***, **, * show significance at the 1%, 5% and 10% levels respectively.
Standard errors are presented in parentheses
[a] McGill University is the omitted dummy variable

Table

Table 2 – Negative binomial regression results – number of articles per academic per year (distinguishing operating cost and infrastructure grants)

Model	Panel	X-section	Panel Two-Stage Residual Inclusion (2SRI)						X-section 2SRI	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Average amount of operating costs grants over the past 3 years										
ln($AveGrantO3_{t-1}$)	-0.0714 ***	-0.1004 ***	0.0599 ***	0.0633 ***	0.0451 ***	-0.0147	-0.0343	-0.0331	0.1550 ***	0.0543 *
	(0.0154)	(0.0201)	(0.0149)	(0.0147)	(0.0135)	(0.0246)	(0.0231)	(0.0231)	(0.0231)	(0.0319)
[ln($AveGrantO3_{t-1}$)]^2	0.0061 ***	0.0094 ***				0.0052 ***	0.0055 ***	0.0055 ***		0.0064 ***
	(0.0013)	(0.0017)				(0.0013)	(0.0013)	(0.0013)		(0.0017)
Average amount of contracts over the past 3 years										
ln($AveCont3_{t-1}$)	-0.0090	-0.0031	0.0020	0.0029	0.0052	-0.0107	-0.0105	-0.0132	-0.0042	-0.0173
	(0.0136)	(0.0186)	(0.0034)	(0.0033)	(0.0034)	(0.0136)	(0.0136)	(0.0136)	(0.0051)	(0.0181)
[ln($AveCont3_{t-1}$)]^2	0.0014	0.0008				0.0011	0.0015	0.0015		0.0009
	(0.0013)	(0.0018)				(0.0013)	(0.0013)	(0.0013)		(0.0017)
Number of patent applications of the past 3 years										
$nbPatent3_{t-1}$	0.0789 ***	0.0913 ***	0.0174 ***	-0.0039	0.0511 ***	0.0696 ***	0.0602 ***	0.0842 ***	0.0535 ***	0.0998 ***
	(0.0136)	(0.0208)	(0.0044)	(0.0049)	(0.0084)	(0.0110)	(0.0116)	(0.0137)	(0.0131)	(0.0195)
[$nbPatent3_{t-1}$]^2	-0.0012 **	-0.0020 ***				-0.0016 ***	-0.0007	-0.0014 **		-0.0024 ***
	(0.0005)	(0.0008)				(0.0002)	(0.0005)	(0.0005)		(0.0008)
3-year network betweenness centrality										
$Btwness3_{t-2}$ x10^4	0.0424 ***	0.1231 ***		0.0102 ***	0.0397 ***	0.0111 ***	0.0412 ***	0.0415 ***	0.0981 ***	0.1094 ***
	(0.0067)	(0.0146)		(0.0011)	(0.0066)	(0.0011)	(0.0067)	(0.0067)	(0.0177)	(0.0145)
3-year network cliquishness										
ln($Cliqness3_{t-2}$x10^4)	0.0703 **	0.2080 ***	-0.0044 *	-0.0048 *	-0.0042 *	0.0512 *	0.0789 **	0.0722 **	-0.0140 ***	0.2254 ***
	(0.0309)	(0.0449)	(0.0025)	(0.0025)	(0.0025)	(0.0300)	(0.0309)	(0.0309)	(0.0024)	(0.0448)
[ln($Cliqness3_{t-2}$x10^4)]^2	-0.0025 **	-0.0075 ***				-0.0019 *	-0.0028 ***	-0.0026 **		-0.0080 ***
	(0.0010)	(0.0015)				(0.0010)	(0.0010)	(0.0010)		(0.0015)
Nanotechnology 'career' age of an academic										
Age_t	0.0859 ***	0.0472 **	0.0267 ***	0.0198 ***	0.0187 ***	0.0599 ***	0.0664 ***	0.0651 ***	-0.0126 *	-0.0060
	(0.0160)	(0.0184)	(0.0069)	(0.0067)	(0.0064)	(0.0188)	(0.0183)	(0.0183)	(0.0066)	(0.0206)
Age_t^2	-0.0026 ***	-0.0018 **				-0.0018 ***	-0.0020 ***	-0.0020 ***		-0.0004
	(0.0006)	(0.0007)				(0.0007)	(0.0007)	(0.0006)		(0.0008)
Interaction variables										
($Btwness3_{t-2}$x10^4) x	-0.0047 ***	-0.0154 ***			-0.0042 ***		-0.0046 ***	-0.0045 ***	-0.0105 ***	-0.0131 ***
ln($Cliqness3_{t-2}$x10^4)	(0.0010)	(0.0024)			(0.0010)		(0.0010)	(0.0010)	(0.0030)	(0.0024)
($Btwness3_{t-2}$x10^4) x	0.0002	0.0009 **			-0.0001		-0.0002	0.0002	0.0005	0.0007 *
ln($AveCont3_{t-1}$)	(0.0002)	(0.0004)			(0.0001)		(0.0002)	(0.0002)	(0.0006)	(0.0004)
($Btwness3_{t-2}$x10^4) x	-0.0017 ***	-0.0036 ***			-0.0005 ***		-0.0002 *	-0.0019 ***	-0.0009 ***	-0.0039 ***
$nbPatent3_{t-1}$	(0.0005)	(0.0007)			(0.0001)		(0.0001)	(0.0005)	(0.0001)	(0.0007)

Model	**Panel**	**X-section**	**Panel Two-Stage Residual Inclusion (2SRI)**						**X-section 2SRI**	
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
($Btwness3_{t-2}$x10^4) x	2.7E-05 ***	6.0E-05 ***						3.0E-05 ***		6.5E-05 ***
[$nbPatent3_{t-1}$]^2	(0.9E-05)	(1.3E-05)						(0.9E-05)		(1.3E-05)
Universities dummy variables [a]										
dULaval	-0.2125 ***	-0.0769	-0.3303 ***	-0.2984 ***	-0.2534 ***	-0.2702 ***	-0.2364 ***	-0.2325 ***	-0.1854 ***	-0.1522 ***
	(0.0632)	(0.0575)	(0.0722)	(0.0676)	(0.0652)	(0.0655)	(0.0639)	(0.0636)	(0.0609)	(0.0578)
dUMontrealG	-0.2311 ***	-0.0956 *	-0.3406 ***	-0.2868 ***	-0.2573 ***	-0.2714 ***	-0.2396 ***	-0.2393 ***	-0.1779 ***	-0.1546 ***
	(0.0597)	(0.0542)	(0.0674)	(0.0634)	(0.0613)	(0.0614)	(0.0601)	(0.0598)	(0.0562)	(0.0533)
dUConcordia	-0.1302	-0.1282	-0.0654	-0.1391	-0.1279	-0.1252	-0.0979	-0.1010	-0.0742	-0.0311
	(0.1196)	(0.1337)	(0.1389)	(0.1282)	(0.1231)	(0.1243)	(0.1207)	(0.1203)	(0.1264)	(0.1335)
dUSherbrokkeG	-0.3078 ***	-0.1531 **	-0.4759 ***	-0.4139 ***	-0.3633 ***	-0.3560 ***	-0.3166 ***	-0.3156 ***	-0.2617 ***	-0.1997 ***
	(0.0830)	(0.0705)	(0.0933)	(0.0879)	(0.0849)	(0.0856)	(0.0837)	(0.0833)	(0.0715)	(0.0706)
dUQuebecG	-0.3186 ***	-0.1396 *	-0.4336 ***	-0.3735 ***	-0.3456 ***	-0.3383 ***	-0.3104 ***	-0.3091 ***	-0.1637 *	-0.1246 *
	(0.0728)	(0.0748)	(0.0813)	(0.0765)	(0.0739)	(0.0747)	(0.0732)	(0.0728)	(0.0740)	(0.0704)
Residuals from 1st stage			-0.0623 ***	-0.0663 ***	-0.0466 ***	-0.0491 ***	-0.0325 **	-0.0336 **	-0.1506 ***	-0.1586 ***
			(0.0155)	(0.0153)	(0.0142)	(0.0160)	(0.0149)	(0.0148)	(0.0237)	(0.0239)
Constant	1.3428 ***	-0.2252	1.6480 ***	1.5411 ***	1.6318 ***	1.2716 ***	1.1813 ***	1.2011 ***	-0.3025	-1.0866 ***
	(0.1941)	(0.2275)	(0.1536)	(0.1516)	(0.1452)	(0.2054)	(0.2056)	(0.2054)	(0.1969)	(0.2863)
Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ln(r)	2.6922 ***		2.4052 ***	2.5413 ***	2.6318 ***	2.6376 ***	2.6888 ***	2.7039 ***		
	(0.0837)		(0.0797)	(0.0814)	(0.0826)	(0.0831)	(0.0838)	(0.0842)		
ln(s)	1.5479 ***		1.1839 ***	1.3658 ***	1.4730 ***	1.4617 ***	1.5400 ***	1.5548 ***		
	(0.0803)		(0.0661)	(0.0726)	(0.0765)	(0.0765)	(0.0802)	(0.0807)		
ln(alpha)		-0.9475 ***							-0.9196 ***	-0.9895 ***
		(0.0566)							(0.0533)	(0.0543)
Nb observations	5741	5741	5710	5710	5710	5710	5710	5710	5710	5710
Nb academics	907	907	906	906	906	906	906	906	906	906
Average nb years	6.33	6.33	6.30	6.30	6.30	6.30	6.30	6.30	6.30	6.30
Log likelihood	-11012.1	-11401.1	-11043.6	-11007.8	-10976.1	-10963.4	-10952.7	-10947.1	-11367.5	-11297.9
Wald χ^2	450.75 ***	5036.74 ***	221.99 ***	397.00 ***	419.87 ***	447.60 ***	447.60 ***	463.05 ***	727.03 ***	5477.35 ***

Notes: ***, **, * show significance at the 1%, 5% and 10% levels respectively.

Standard errors are presented in parentheses

[a] McGill University is the omitted dummy variable

Table

Table B.1 – Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
$nbArticle_t$	5896	2.6109	2.9233	0	32
$nbPatent3_t$	5896	0.4220	1.7908	0	54
$Grant_t$	5896	$260,279	$1,024,648	0	$41,900,000
$GrantO_t$	5896	$184,347	$328,426	$84	$6,738,504
$GrantI_t$	5896	$75,932	$910,158	0	$41,600,000
$Cont_t$	5896	$45,809	$392,464	0	$12,100,000
$AveGrant3_t$	5896	$233,503	$707,174	0	$15,900,000
$AveGrantO3_t$	5896	$166,769	$292,962	$91	$5,180,839
$AveGrantI3_t$	5896	$66,735	$553,134	0	$15,200,000
$AveCont3_t$	5896	$43,942	$367,643	0	$11,600,000
$\ln(AveGrant3_t)$	5894	11.4137	1.3499	4.5248	16.5820
$\ln(AveGrantO3_t)$	5896	11.2812	1.2808	4.5248	15.4605
$\ln(AveGrantI3_t)$	5880	3.4135	4.9186	0	16.5350
$\ln(AveCont3_t)$	5891	3.9198	5.0198	0	16.2668
$Btwness3_t$	5896	3.662E-04	9.058E-04	0	2.022E-02
$Cliqness3_t$	5896	0.0157	0.0472	0	0.7243
codeChair	5896	0.6530	0.8845	0	3
Age_t	5896	12.7473	4.3708	1	21

Table

Table B.2 – Correlation matrix

Variable		1	2	3	4	5	6	7	8	9	10	11
$nbArticle_t$	1	1										
$AveArticle3_{t\text{-}2}$	2	0.6283	1									
$nbPatent3_{t\text{-}1}$	3	0.1361	0.2340	1								
$\ln(AveGrant3_{t\text{-}1})$	4	0.0898	0.1499	0.0560	1							
$\ln(AveGrantO3_{t\text{-}1})$	5	0.0937	0.1550	0.0562	0.9842	1						
$\ln(AveGrantI3_{t\text{-}1})$	6	0.0513	0.0201	0.0554	0.3478	0.2743	1					
$\ln(AveCont3_{t\text{-}1})$	7	0.0893	0.0890	0.1103	0.2712	0.2701	0.1553	1				
$Btwness3_{t\text{-}2}\text{x}10^4$	8	0.4905	0.7283	0.3123	0.0219	0.0280	-0.0261	0.0109	1			
$\ln(Cliqness3_{t\text{-}2}\text{x}10^4)$	9	-0.1052	-0.2421	-0.0232	-0.0550	-0.0565	-0.0154	-0.0181	-0.0809	1		
codeChair	10	0.0436	0.0570	-0.0043	0.1735	0.1749	0.1346	0.1178	0.0158	-0.0155	1	
Age_t	11	0.1450	0.2598	0.0611	0.3053	0.3140	0.0696	0.1366	0.0937	-0.0756	0.0930	1

Table

Table C.1 – First stage regressions results – average amount of grant funding received over three years per academic per year

	Panel Two-Stage Residual Inclusion (2SRI)						X-section 2SRI	
Variables	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Instruments								
Average number of articles published per year in the past 3-5 years								
AveArticle3$_{t-2}$	0.0479 **	0.0740 **	0.0572 *	0.0698 **	0.0491	0.0497	0.1497 ***	0.1673 ***
	(0.0243)	(0.0309)	(0.0327)	(0.0310)	(0.0330)	(0.0330)	(0.0310)	(0.0308)
Ordinal variable of the 'best' Chair occupied by an academic								
codeChair	0.5703 ***	0.5683 ***	0.5675 ***	0.5712 ***	0.5714 ***	0.5710 ***	0.3970 ***	0.3935 ***
	(0.0952)	(0.0947)	(0.0947)	(0.0945)	(0.0946)	(0.0947)	(0.0539)	(0.0539)
Average amount of grants received by nanotechnology colleagues at the same university of an academic over the past 3 years								
ln(AveGrant3U$_{t-1}$)	1.7939 ***	1.7866 ***	1.7769 ***	1.7172 ***	1.7110 ***	1.7101 ***	1.4855 ***	1.4674 ***
	(0.1124)	(0.1125)	(0.1125)	(0.1121)	(0.1121)	(0.1121)	(0.1758)	(0.1741)
Variables from the second stage equation								
ln($AveCont3_{t-1}$)	0.0975 ***	0.0971 ***	0.0942 ***	0.0896 **	0.0904 **	0.0921 **	0.1152 ***	0.0967 ***
	(0.0096)	(0.0096)	(0.0102)	(0.0449)	(0.0449)	(0.0450)	(0.0093)	(0.0408)
[ln($AveCont3_{t-1}$)]^2				0.0004	-0.0001	-0.0001		0.0016
				(0.0042)	(0.0043)	(0.0043)		(0.0038)
$nbPatent3_{t-1}$	0.0318	0.0394	0.0095	-0.0094	-0.0103	-0.0246	-0.0014	-0.0270
	(0.0236)	(0.0243)	(0.0328)	(0.0422)	(0.0456)	(0.0509)	(0.0260)	(0.0487)
[$nbPatent3_{t-1}$]^2				0.0013	0.0010	0.0014		0.0014
				(0.0010)	(0.0020)	(0.0021)		(0.0016)
$Btwness3_{t-2}$x10^4		-0.0093	0.0324	-0.0152 **	0.0315	0.0314	0.0220	0.0003
		(0.0069)	(0.0353)	(0.0071)	(0.0358)	(0.0358)	(0.0380)	(0.0384)
ln($Cliqness3_{t-2}$x10^4)	0.0015	0.0024	0.0021	-0.0525	-0.0274	-0.0235	-0.0002	-0.2591 **
	(0.0064)	(0.0064)	(0.0064)	(0.0909)	(0.0934)	(0.0936)	(0.0071)	(0.1051)
[ln($Cliqness3_{t-2}$x10^4)]^2				0.0019	0.0010	0.0009		0.0087 **
				(0.0031)	(0.0031)	(0.0032)		(0.0036)
Age_t	0.1775 ***	0.1769 ***	0.1776 ***	0.5630 ***	0.5656 ***	0.5658 ***	0.1351 ***	0.3668 ***
	(0.0204)	(0.0203)	(0.0204)	(0.0494)	(0.0494)	(0.0494)	(0.0143)	(0.0662)
Age_t^2				-0.0162 ***	-0.0164 ***	-0.0164 ***		-0.0094 ***
				(0.0019)	(0.0019)	(0.0019)		(0.0025)
Interaction variables								
($Btwness3_{t-2}$x10^4) x ln($Cliqness3_{t-2}$x10^4)			-0.0072		-0.0078	-0.0079	-0.0084	-0.0048
			(0.0054)		(0.0055)	(0.0055)	(0.0060)	(0.0061)

Variables	Panel Two-Stage Residual Inclusion (2SRI) (3)	(4)	(5)	(6)	(7)	(8)	X-section 2SRI (9)	(10)
($Btwness3_{t-2}$x10^4) x			0.0010		0.0012	0.0009	0.0006	0.0005
ln($AveCont3_{t-1}$)			(0.0008)		(0.0008)	(0.0009)	(0.0006)	(0.0008)
($Btwness3_{t-2}$x10^4) x			0.0004		0.0001	0.0016	0.0007 ***	0.0020
$nbPatent3_{t-1}$			(0.0003)		(0.0006)	(0.0025)	(0.0002)	(0.0023)
($Btwness3_{t-2}$x10^4) x						-2.8E-05		-3.2E-05
$[nbPatent3_{t-1}]^2$						(4.4E-05)		(4.0E-05)
Universities dummy variables [a]								
dULaval	-0.1296	-0.1264	-0.1159	-0.1534	-0.1403	-0.1418	0.0303	0.0370
	(0.2501)	(0.2488)	(0.2491)	(0.2483)	(0.2489)	(0.2490)	(0.1517)	(0.1520)
dUMontrealG	-0.2151	-0.2196	-0.2041	-0.2148	-0.2027	-0.2018	0.0306	0.0590
	(0.23433)	(0.2331)	(0.2334)	(0.2328)	(0.2333)	(0.2334)	(0.1453)	(0.1471)
dUConcordia	0.4084	0.4377	0.4667	0.3722	0.3961	0.3858	0.4566	0.4597
	(0.4494)	(0.4479)	(0.4482)	(0.4469)	(0.4475)	(0.4477)	(0.3967)	(0.3951)
dUSherbrookeG	0.2543	0.2542	0.2579	0.2254	0.2346	0.2340	0.3183 *	0.3241 *
	(0.3205)	(0.3188)	(0.3190)	(0.3182)	(0.3182)	(0.3189)	(0.1764)	(0.1783)
dUQuebecG	-0.1840	-0.1890	-0.1784	-0.2777	-0.2664	-0.2663	-0.1812	-0.1842
	(0.2780)	(0.2766)	(0.2770)	(0.2764)	(0.2770)	(0.2771)	(0.1727)	(0.1731)
Constant	-13.1000 ***	-13.0000 ***	-12.9000 ***	-14.1000 ***	-14.1000 ***	-14.2000 ***	-8.6258 ***	-8.5984 ***
	(1.2675)	(1.2684)	(1.2695)	(1.3342)	(1.3360)	(1.3360)	(1.9557)	(1.9991)
Years	yes	yes	yes	yes	yes	yes	yes	yes
Nb observations	5724	5724	5724	5724	5724	5724	5724	5724
Nb academics	907	907	907	907	907	907	907	907
Average nb years	6.31	6.31	6.31	6.31	6.31	6.31	6.31	6.31
F							80.61 ***	364.11 ***
Wald χ^2	2127.23 ***	2127.69 ***	2133,52 ***	2235.94 ***	2241.37 ***	2241.67 ***		
R^2 overall	0.2522	0.2537	0.2547	0.2557	0.2562	0.2563	0.2627	0.2674
R^2 within groups	0.2926	0.2921	0.2926	0.3060	0.3067	0.3067		
R^2 between groups	0.1301	0.1343	0.1355	0.1251	0.1247	0.1250		

Notes: ***, **, * show significance at the 1%, 5% and 10% levels respectively.
Standard errors are presented in parentheses
[a] McGill University is the omitted university

Table

Table C.2 – First stage regressions results – average amount of operating costs funding received over three years per academic per year

	Panel Two-Stage Residual Inclusion (2SRI)						X-section 2SRI	
Variables	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Instruments								
Average number of articles published per year in the past 3-5 years								
$AveArticle3_{t\text{-}2}$	0.0440 *	0.0644 **	0.0504	0.0647 **	0.0458	0.0465	0.1405 ***	0.1580 ***
	(0.0237)	(0.0302)	(0.0318)	(0.0303)	(0.0321)	(0.0321)	(0.0287)	(0.0289)
Ordinal variable of the 'best' Chair occupied by an academic								
codeChair	0.4886 ***	0.4871 ***	0.4785 ***	0.4899 ***	0.4829 ***	0.4825 ***	0.3305 ***	0.3272 ***
	(0.0916)	(0.0913)	(0.0915)	(0.0912)	(0.0915)	(0.0915)	(0.0522)	(0.0516)
Average amount of grants received by nanotechnology colleagues at the same university of an academic over the past 3 years								
$\ln(AveGrant3U_{t\text{-}1})$	1.6484 ***	1.6425 ***	1.6279 ***	1.5746 ***	1.5631 ***	1.5621 ***	1.2934 ***	1.2737 ***
	(0.1104)	(0.1105)	(0.1097)	(0.1100)	(0.1093)	(0.1093)	(0.1709)	(0.1694)
Variables from the second stage equation								
$\ln(AveGrantI3_{t\text{-}1})$	0.1164 ***	0.1162 ***	0.1804 ***	0.1948 ***	0.1912 ***	0.1905 ***		-0.0030
	(0.0089)	(0.0089)	(0.0111)	(0.0395)	(0.0393)	(0.0393)		(0.0026)
$[\ln(AveGrantI3_{t\text{-}1})]^2$				-0.0073 **	-0.0013	-0.0013	0.1636 ***	0.1959 ***
				(0.0036)	(0.0036)	(0.0036)	(0.0107)	(0.0295)
$\ln(AveCont3_{t\text{-}1})$	0.0910 ***	0.0907 ***	0.1362 ***	0.0723	0.1065 **	0.1083 **	0.1356 ***	0.0947 **
	(0.0094)	(0.0094)	(0.0112)	(0.0440)	(0.0439)	(0.0440)	(0.0109)	(0.0372)
$[\ln(AveCont3_{t\text{-}1})]^2$				0.0016	0.0022	0.0022		0.0038
				(0.0041)	(0.0041)	(0.0041)		(0.0035)
$nbPatent3_{t\text{-}1}$	0.0359	0.0419 *	0.0030	-0.0411	-0.0333	-0.0483	-0.0193	-0.0771
	(0.0232)	(0.0238)	(0.0320)	(0.0414)	(0.0445)	(0.0497)	(0.0280)	(0.0480)
$[nbPatent3_{t\text{-}1}]^2$				0.0022 **	0.0019	0.0024		0.0033 **
				(0.0009)	(0.0019)	(0.0020)		(0.0017)
$Btwness3_{t\text{-}2}\text{x}10^4$		-0.0073	0.0282	-0.0147 **	0.0234	0.0233	0.0057	-0.0124
		(0.0068)	(0.0344)	(0.0070)	(0.0349)	(0.0349)	(0.0360)	(0.0369)
$\ln(Cliqness3_{t\text{-}2}\text{x}10^4)$	0.0003	0.0010	-0.0010	-0.0912	-0.0999	-0.0959	-0.0026	-0.2374 **
	(0.0063)	(0.0063)	(0.0063)	(0.0891)	(0.0910)	(0.0912)	(0.0067)	(0.0979)
$[\ln(Cliqness3_{t\text{-}2}\text{x}10^4)]^2$				0.0031	0.0033	0.0032		0.0079 **
				(0.0030)	(0.0031)	(0.0031)		(0.0033)
Age_t	0.2107 ***	0.2102 ***	0.2151 ***	0.6137 ***	0.6051 ***	0.6053 ***	0.1643 ***	0.4125 ***
	(0.0197)	(0.0196)	(0.0197)	(0.0484)	(0.0482)	(0.0482)	(0.0140)	(0.0639)
Age_t^2				-0.0165 ***	-0.0160 ***	-0.0160 ***		-0.0101 ***
				(0.0018)	(0.0018)	(0.0018)		(0.0024)
Interaction variables								

	Panel Two-Stage Residual Inclusion (2SRI)						X-section 2SRI	
Variables	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
(*$Btwness3_{t-2}$* x10^4) x			-0.0064		-0.0061	-0.0062	-0.0054	-0.0024
ln(*$Cliqness3_{t-2}$*)			(0.0053)		(0.0054)	(0.0054)	(0.0057)	(0.0058)
ln(*$AveGrantI3_{t-2}$*) x			-0.0142 ***		-0.0135 ***	-0.0135 ***	-0.0091 ***	-0.0090 ***
ln(*$AveCont3_{t-1}$*)			(0.0015)		(0.0015)	(0.0015)	(0.0012)	(0.0013)
(*$Btwness3_{t-2}$* x10^4) x			0.0009		0.0011	0.0008	0.0005	0.0003
ln(*$AveCont3_{t-1}$*)			(0.0008)		(0.0008)	(0.0009)	(0.0006)	(0.0007)
(*$Btwness3_{t-2}$* x10^4) x			0.0004		-0.0001	0.0015	0.0008 ***	0.0026
$nbPatent3_{t-1}$			(0.0003)		(0.0006)	(0.0024)	(0.0002)	(0.0022)
(*$Btwness3_{t-2}$* x10^4) x						-2.9E-05		-4.8E-05
[*$nbPatent3_{t-1}$*]^2						(4.3E-05)		(4.0E-05)
Universitiy dummy variables [a]								
dULaval	-0.3757	-0.3730	-0.3812	-0.4153 *	-0.3994 *	-0.4008 *	-0.2601 *	-0.2558 *
	(0.2409)	(0.2400)	(0.2407)	(0.2399)	(0.2408)	(0.2408)	(0.1516)	(0.1526)
dUMontrealG	-0.4244 *	-0.4276 *	-0.4515 **	-0.4190 *	-0.4418 *	-0.4409 *	-0.1840	-0.1484
	(0.2256)	(0.2248)	(0.2254)	(0.2246)	(0.2254)	(0.2254)	(0.1458)	(0.1473)
dUConcordia	0.3623	0.3848	0.4396	0.3293	0.3812	0.3810	0.2880	0.2903
	(0.4332)	(0.4324)	(0.4328)	(0.4317)	(0.4323)	(0.4323)	(0.3588)	(0.3511)
dUSherbrookeG	-0.0698	-0.0700	-0.0761	-0.1224	-0.0973	-0.0978	-0.0874	-0.0831
	(0.3086)	(0.3074)	(0.3082)	(0.3074)	(0.3084)	(0.3083)	(0.1716)	(0.1731)
dUQuebecG	-0.3518	-0.3559	-0.3867	-0.4541 *	-0.4617 *	-0.4616 *	-0.4447 ***	-0.4482 ***
	(0.2673)	(0.2663)	(0.2672)	(0.2665)	(0.2674)	(0.2674)	(0.1562)	(0.1568)
Constant	-11.8000 ***	-11.7000 ***	-11.7000 ***	-12.7000 ***	-12.6000 ***	-12.6000 ***	-6.8274 ***	-6.9823 ***
	(1.2449)	(1.2459)	(1.2375)	(1.3097)	(1.3030)	(1.3031)	(1.8960)	(1.9309)
Years	yes	yes	yes	yes	yes	yes	yes	yes
Nb observations	5710	5710	5710	5710	5710	5710	5710	5710
Nb academics	906	906	906	906	906	906	906	906
Average nb years	30	30	30	30	30	30	30	30
F							95.27 ***	452.41 ***
Wald c^2	2308.71 ***	2308.92 ***	2443.96 ***	2442.29 ***	2560.28 ***	2560.46 ***		
R^2 overall	0.2792	0.2802	0.2850	0.2848	0.2885	0.2886	0.2947	0.3003
R^2 within groups	0.3047	0.3062	0.3205	0.3216	0.3341	0.3341		
R^2 between groups	0.1700	0.1737	0.1744	0.1668	0.1657	0.1661		

Notes: ***, **, * show significance at the 1%, 5% and 10% levels respectively. Standard errors are presented in parentheses

[a] McGill University is the omitted university